

Fuzzy Continuous Review Inventory Model using ABC Multi-Criteria Classification Approach: A Single Case Study

Julita and Meriastuti Ginting*

Industrial & System Engineering Department, Krida Wacana Christian University - Jakarta

Abstract. Inventory is considered as the most expensive, yet important, to any companies. It represents approximately 50% of the total investment. Inventory cost has become one of the major contributors to inefficiency, therefore it should be managed effectively. This study aims to propose an alternative inventory model, by using ABC multi-criteria classification approach to minimize total cost. By combining FANP (Fuzzy Analytical Network Process) and TOPSIS (Technique of Order Preferences by Similarity to the Ideal Solution), the ABC multi-criteria classification approach identified 12 items of 69 inventory items as "outstanding important class" that contributed to 80% total inventory cost. This finding is then used as the basis to determine the proposed continuous review inventory model. This study found that by using fuzzy trapezoidal cost, the inventory turnover ratio can be increased, and inventory cost can be decreased by 78% for each item in "class A" inventory.

Keywords: ABC multi-criteria classification, FANP-TOPSIS, continuous review inventory model lead-time demand distribution, trapezoidal fuzzy number

1. Introduction

Inventory is considered as the most expensive, yet important, to any companies. It represents approximately 50% of the total investment (Balakrishnan et al., 2011: 12-2). Inventory cost has become one of the major contributors to inefficiency, therefore it should be managed effectively and efficiently to minimize the total cost. In this case, the design of an appropriate inventory model with real life situations is in need (Nahmias, 2004: 275).

The main factor that should be noted in designing the inventory model is that items held in inventory is not equal importance of money invested, profit potential, sales volume, or stock out penalties (Godwin et al., 2013). In real life, differences in importance generally seen as opportunities to distinguish a limited number of inventory items in several classes known as inventory classification (Kampen et al., 2012). A well-known approach to inventory classifications is the ABC analysis, which classifies the

inventory items based on Pareto principle. ABC analysis divides the inventory into three classes: A – outstandingly important, B – of average importance, and C – relatively unimportant. Each class should be handled in a different way, with more attention being devoted to category A, less to B, and less to C (Nahmias, 2004: 276).

This study intends to propose an appropriate inventory model using multi-criteria classification approaches and focuses on determining the inventory model for class A items which is obtained from the multi-criteria classification result.

2. Literature Review

2.1. Multi-Criteria Inventory Classification

In order to create an inventory classification, two basic questions to answer are how many classes are used and how the borders between the classes are determined (Kampen et al., 2012). There is no fixed rule for the number of classes used in the inventory classification. Previous researchers had shown that using three classes of

*Corresponding author. Email: meriastuti.ginting@ukrida.ac.id

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inventory classification is the optimal number and it is familiar to managers. The number of inventory items does not affect the determination or a determination of the number of classes. Rezaei *et al.* (2010), Torabi *et al.* (2012), Keskin *et al.* (2013) classify the raw materials amounting to an average of 50 items into three classes; Kabir *et al.* (2012) classifies 315 raw materials of construction industry into three classes; and Kartal *et al.* (2012) classifies 715 raw materials of automotive industry into three classes as well. Therefore, this study classified the inventory items into three classes: A (outstandingly important), B (of average importance), and C (relatively unimportant).

Determination of the borders between the classes affected by the classification criteria and classification techniques (Kampen *et al.*, 2012). The traditional ABC classification has generally been based on just one criterion, the annual dollar usage. However, using single criteria are irrelevant in real life. Yu (2010) and Keskin *et al.* (2013) revealed that using the annual dollar usage criterion only might create problems of significant financial loss because there are other important criteria that should be considering such as lead-time, criticality, durability, and so on. Thus, to get the inventory classification criteria, which are relevant to the subject of this research, the study gives authority on managers to choose their own criteria. To assist the selection criteria process, the master list of criteria that have been used in academic researchers are provided.

Multi-criteria inventory classification is a part of Multi-criteria Decision Making (MCDM) problems. Kampen *et al.* (2012) distinguished this MCDM technique into two types based on the knowledge source: the statistical and judgmental techniques. Statistical techniques knowledge sources are based on data of a number of inventory items characteristics. Yu (2010) and Fernandez *et al.* (2011) used the statistical

techniques in classify inventory items. They used metaheuristic approach. The advantage of statistical techniques is the classification result spared from subjectivity. However, these techniques have a high level of complexity. The application of these techniques could be cumbersome for inventory managers especially there is no participation of the manager in it (Rezaei *et al.*, 2010; Kampen *et al.*, 2012).

In contrast to statistical techniques, the judgemental techniques involve the opinions of manager especially in the determination of criteria weights. There are some of the judgemental techniques proposed by previous researchers such as *Technique of Order Preferences by Similarity to The Ideal Solution* (TOPSIS) by Bhattacharya *et al.* (2007), Fuzzy Analytic Hierarchy Process (FAHP) by Kabir *et al.* (2012), combination of Fuzzy Delphi and FAHP by Kabir *et al.* (2013), *Simple Additive Weighting* (SAW) by Kartal *et al.* (2013), and *Fuzzy Analytic Network Process* (FANP) by Kiris (2013).

The main advantage of TOPSIS and SAW technique is that these techniques are practical and suitable for a relatively large amount of inventory. However, these two techniques do not have provisions to determine the weights of criteria. Compared to SAW, TOPSIS has advantages in determining the composite priority weight of alternatives that takes into account the closest distance from the positive ideal solution. The main advantage of AHP is this technique has consistency consideration in determining the weights of each criterion in which it can cover up the weakness of TOPSIS. However, the FAHP is still having an element of subjectivity and assumption that each criterion is independent. Therefore, the extended version of FAHP technique, namely FANP can cover up the weakness of FAHP because this technique considers the dependency factor among criteria and it produces a more stable weight than FAHP. Based on the advantages and disadvantages of the above techniques, this

study proposes a combination of FANP and TOPSIS to classify the inventory items.

2.2. Inventory Model

There are two fundamental decisions that should be determined when designing an inventory model. They are when should an order be placed and how much should be ordered (Nahmias, 2004: 193; Balakrishnan *et al.*, 2011: 12-3 - 12-4). The complexity of the resulting inventory model depends upon the assumptions one makes about the various variables of the system. The variables are demand, lead-time, excess demand, inventory costs, and review time (Nahmias, 2004: 193-197). The determination of the characteristics of these variables needs to adjust to the research subject because the proposed model is designing not only to describe the situation of a system but also provides the best answer to the inventory problem.

Demand variable is distinguished into two types: known demand (deterministic model) and uncertain (stochastic model) (Nahmias, 2004:196). According to the condition of the subject of research, this study uses uncertain demand model. It means that the exact number of future demand cannot be predicted at the beginning. The uncertain demand variable is influenced by lead-time variable (Nahmias, 2004:197). In this case, although the future demand cannot be predicted at the beginning, one's past experience can provide useful information for planning. The random demand on the past can be used to estimate its lead-time demand probability distribution. Previous researchers generally assumed the lead time demand distribution is uniform for all inventory items, such as entirely normal distribution (Silver *et al.*, 2011, Joshi *et al.*, 2011, Zheng *et al.*, 2011; Sadi-Nezhad *et al.*, 2011) or uniform and exponential distribution (Taleizaideh *et al.*, 2013) without statistical testing, whereas the different type of distribution affects the value of decision variables. For this reason, the study proposes to examine the distribution type of

lead-time demand before formulating the inventory model.

Another important characteristic that determines the inventory model formulation is how the system reacts to excess demand (Nahmias, 2004: 197). In accordance with the subject of research, this study used to apply backorder systems in which the system will satisfy the customer's need in the future.

Determination of inventory models, especially on what variable to be decided is influenced by a review or the review time variable. Review time variables distinguished into two types, continuous review and periodic review (Sipper *et al.*, 1997: 211; Nahmias, 2004: 244). Determining the review time variable should be adjusted to the importance of inventory items on company performance (Nahmias, 2004: 276; Motadel *et al.*, 2012). Previous researchers that considered the importance of inventory item in the review type determination are still limited. Aisyati *et al.* (2013) for example, who designed the continuous review inventory model for class A and B items. Continuous review inventory model considered suitable for class A and B items that have high costs because this model gives the amount of safety stock that is smaller than the periodic review models. In addition, based on the characteristic of continuous review model where fixed quantity ordering, the supplier are easy to predict the order quantity. For these reasons, in accordance with the objective of this study, we propose to use this continuous review inventory model.

Variable that becomes optimization criteria in designing an inventory model is inventory cost. In real life, estimating the exact value of cost variables may not be possible (Sadi-Nezhad *et al.*, 2011; Prasath *et al.*, 2012; Jaggi *et al.*, 2012; Dutta *et al.*, 2012). Inspired by the concept of fuzzy sense, this research proposes to adopt this concept in the cost variable. In the fuzzy sense, two main things

need to be determined. They are the fuzzy membership function and defuzzification technique.

Previous researchers who designed the fuzzy inventory model usually used a triangular and the triangular membership function. For example, Joshi *et al.* (2011), Zheng *et al.* (2011), Sadi-Nezhad *et al.* (2011), Prasath *et al.* (2011), and Jaggi *et al.* (2012) that did not explain why they choose triangular membership function in their research. Dutta *et al.* (2012) examined this uncertainty in the design of EOQ model then. In his research, Dutta *et al.* (2012) found that the trapezoidal membership function gives better results and economical compared to triangular membership function. As well as fuzzy membership function, several previous studies also used defuzzification techniques without a clear explanation of the basis for selection of such techniques. Joshi *et al.* (2011), Zheng *et al.* (2011), and Dutta *et al.* (2012) used signed distance method in their research. Prasath *et al.* (2012) using the centroid method in the research. Finally, Jaggi *et al.* (2012) tried to compare the defuzzification techniques: graded mean

integral representation, signed distance and centroid method in the design of EOQ models. This study proved that the graded mean integral representation technique gives a more economical inventory cost than two other techniques. Based on the findings from Dutta *et al.* (2012) and Jaggi *et al.* (2012), this study will use trapezoidal membership functions and graded mean integral representation defuzzification technique in stochastic inventory model environment.

3. Methodology

This study is an applied quantitative case study research. This study tried to investigate (in depth) the inventory management in a food supplement company and find a solution, the appropriate inventory model for the company. This study emphasizes the development of the theory by measuring the variables in numbers and performs data analysis with a systematic modeling. This study was developed through several steps. The steps are schematically described in the workflow of this research in Figure 1.

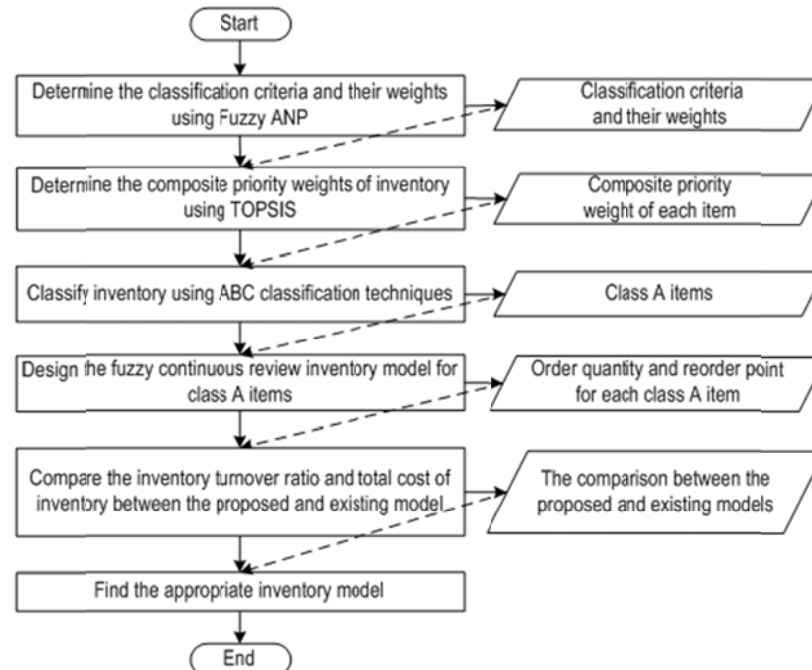


Figure 1. Research Workflow

The first step, determine the classification criteria and their weights. Classification criteria were collected by conducting semi-structured interviews with the Supply Chain Group Head of Indocare Citrapasific Enterprise. After determining the relevant criteria, semi-structured interviews for the weight of criteria and the dependence of each criterion with the pair wise comparison technique was conducted. This study used five fuzzy scales defined by Kahraman *et al.* (2006) as seen in Table 1. Linguistic variables are primarily used to assess the

linguistic ratings given by decision maker for pairwise comparisons of the importance of the criteria in FANP. A selection or the selection of five scales is intended that the decision maker has relatively many choices that do not affect big errors of judgment. The Fuzzy Analytic Network Process (FANP) approach in which Mikhailov's fuzzy preference programming was used to determine the weights of fuzzy comparison matrices. The weights of the classification criteria were determined in this step.

Table 1. Fuzzy Linguistic Scales of Importance

Linguistic scales of importance	Triangular fuzzy scales	Triangular fuzzy reciprocal scales
Just equal	(1,1,1)	(1,1,1)
Equally important	(1/2,1,3/2)	(2/3,1,2)
Weakly more important	(1,3/2,2)	(1/2,2/3,1)
Strongly more important	(3/2,2,5/2)	(2/5, 1/2 ,2/3)
Very strongly more important	(2,5/2,3)	(1/3,2/5,1/2)
Absolutely more important	(5/2,3,7/2)	(2/7,1/3,2/5)

Source: Kahraman, Ertay, Buyukozkan, 2006, *A Fuzzy Optimization Model for QFD Planning Process Using Analytic Network Approach*, 398.

The second step, determine the composite priority weights of inventory items and classify the items. Data of each inventory item based on the selected criteria was collected by archiving. TOPSIS was used to determine the composite priority weight of each item in which the criteria weights were already obtained from the previous step. Traditional ABC classification technique was used to classify the inventory items into three classes. In this case, the supply chain manager of the company determined the borders between the classes.

The third step, design the mathematical formulation of a fuzzy or the fuzzy continuous review inventory model for class A items. Previously, the pattern of lead-time demand distribution was tested by using the Arena Input Analyzer software. Data of expected inventory costs such as unit cost, holding cost, ordering cost and penalty cost in the trapezoidal fuzzy number, were collected by archiving and interviewing related employees or managers. In a continuous review inventory model, the estimated total cost of inventory was expressed in equation (1) (Nahmias, 2004: 262; Sadi-Nezhad *et al.*, 2011).

$$C(Q,r) = \frac{k\lambda}{Q} + h \left[\frac{Q}{2} + R - \lambda\tau \right] + \left(\frac{p\lambda}{Q} n(R) \right) + \lambda c \dots \dots \dots (1)$$

Where:

$C(Q,r)$ = total inventory cost

k = ordering cost

- λ = annual demand
 Q = optimal order quantity
 h = holding cost
 R = reorder point quantity
 $\lambda\tau$ = demand during lead time
 p = penalty cost
 c = unit cost
 $n(R)$ = expected stock out demand per cycle is defined in equation (2):

$$n(R) = \int_R^{\infty} (x - R) f(x) dx \dots \dots \dots (2)$$

Where, $f(x)$ is the probability density function of the lead-time demand distribution.

Because we use trapezoidal membership function for variable cost, then the variable will be as follows:

= ordering cost in trapezoidal fuzzy number = k_1, k_2, k_3, k_4

= holding cost in trapezoidal fuzzy number = h_1, h_2, h_3, h_4

= penalty cost in trapezoidal fuzzy number = p_1, p_2, p_3, p_4

By using graded mean integral representation techniques, the defuzzification value of a fuzzy set $A = (a, b, c, d)$ in h level is formulated in equation (3) (Rezvani, 2013).

$$\begin{aligned}
 G(A) &= \int_0^1 \left[\frac{(a+d)h + (b-a-d+c)h^2}{2} \right] dh / \int_0^1 h dh \\
 &= \left[\frac{(a+d)}{4} + \frac{(b-a-d+c)}{6} \right] / \frac{1}{2} \\
 &= \left[\frac{(a+d)}{2} + \frac{(b-a-d+c)}{3} \right] \\
 &= \left[\frac{a+2b+2c+d}{6} \right] \dots \dots \dots (3)
 \end{aligned}$$

The trapezoidal fuzzy cost and graded mean integral representation techniques given in equation (3) are substituted into the total cost of inventory in equation (1). Taking the

first derivative of the inventory total cost with respect to Q and R yields the optimal values as seen in equation (4) and (5).

$$Q = \sqrt{\frac{1}{6} \times \left(\frac{2\lambda(k_1 + p_1 n(R))}{h_4} + \frac{4\lambda(k_2 + p_2 n(R))}{h_3} + \frac{4\lambda(k_3 + p_3 n(R))}{h_2} + \frac{2\lambda(k_4 + p_4 n(R))}{h_1} \right)} \dots \dots \dots (4)$$

$$1 - F(R) = \frac{1}{6} \times \left(\frac{Qh_1}{p_4\lambda} + \frac{2Qh_2}{p_3\lambda} + \frac{2Qh_3}{p_2\lambda} + \frac{Qh_4}{p_1\lambda} \right) = \dots \dots \dots (5)$$

Where $F(R)$ is probability that no stock out occurs in the lead time, as seen in equation 6,

$$\int_r^{\infty} f(x) dx = 1 - F(R) \dots \dots \dots (6)$$

The optimum value of Q and R cannot be directly obtained by equation (4) and (5) because those equations are implicit functions that analytically intractable (Bahagia, 2006: 157). Therefore, the iterative procedure suggested by Hadley and Whitin

(1963) is used to solve these equations. This procedure should be repeated until the condition $Q_i = Q_{i-1}$ and $R_i = R_{i-1}$ is met (Nahmias, 2004: 262; Bahagia, 2006: 157-158).

The final step is to evaluate whether the proposed model can solve the inventory problems of the company. Comparison of Inventory Turnover Ratio (ITR) and inventory total cost between the proposed and existing model will be provided. ITR comparison used to evaluate the overstocking level of the proposed model. ITR values obtained from the ratio of demand and average inventory quantity in the warehouse per year. Comparison of the total inventory cost was used to evaluate the

proposed model from a financial or the financial aspect.

4. Results and Discussion

4.1. Inventory Classification

There are four criteria and ten selected sub-criteria that considered relevant to the company. By conducting semi-structured interviews to find out the network of dependencies among the criteria, the model of Analytic Network Process (ANP) is shown in Figure 2.

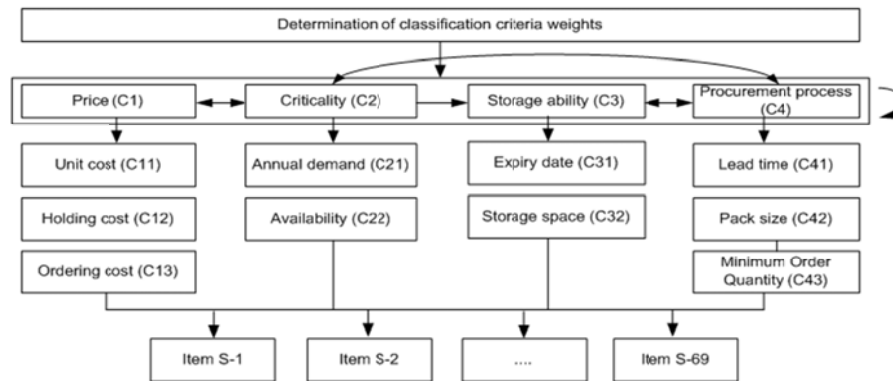


Figure 2. The ANP Model for Classification Criteria Weights

In the first stage the objective is defined. The criteria: price, criticality, storage ability, procurement process are defined in the second stage. The arrow in this stage shows the interdependence among the criteria. For example, based on the model, it could be called the cost and criticality influence each other, the storage capability is influenced by the level of criticality and procurement process. The sub-criteria is shown in the third stage. Table 2 shows the matrix of the pairwise comparison among the criteria in a triangular fuzzy number. For this matrix, the

question asked the decision maker is "What is the importance level between each criterion with respect to the decision goal?" pairwise comparison matrices between sub-criteria also conducted in this study. The local weights of each matrix calculated using Mikhailov's fuzzy preference programming with Lingo 13.0 software. Consistency values (λ) is also measured on the matrix and we found that the entire matrix is consistent ($0 < \lambda \leq 1$). For example, in Table 2, the consistency values (λ) is 0.61 ($0 < \lambda \leq 1$). It means that the matrix is consistent.

Table 2. Local Weights and Pair Wise Comparison Matrix of Criteria

Criteria	C1	C2	C3	C4	Weights
Price (C1)	(1,1,1)	(5/2,3,7/2)	(2,5/2,3)	(3/2,2,5/2)	0.43
Criticality (C2)	(2/7,1/3,2/5)	(1,1,1)	(1/2,2/3,1)	(2/5,1/2,2/3)	0.14
Storage ability (C3)	(1/3,2/5,1/2)	(1,3/2,2)	(1,1,1)	(1/2,2/3,1)	0.19
Procurement process (C4)	(2/5,1/2,2/3)	(3/2,2,5/2)	(1,3/2,2)	(1,1,1)	0.24
					$\lambda = 0.61$

One such dependence matrix of the pair wise comparison is shown in Table 3. It shows the result of criticality criteria as the controlling criterion over other criterions. The semi-structured interview question is

"What criterion is more influential to the criticality criterion: cost or procurement process? How the level of influence of this criterion compared to the other criterion with respect to the criticality?"

Table 3. The Inner Dependence Matrix of The Criteria Based on C2

Criticality (C2)	C1	C4	Relative importance weights
Price (C1)	(1,1,1)	(5/2,3,7/2)	0.75
Procurement process (C4)	(2/7,1/3,2/5)	(1,1,1)	0.25
$\lambda = 0.99$			

Global weights of criteria are computed by multiplying the dependence matrix of the criteria and the local weights of criteria. Global weights of sub-criteria are calculated

by multiplying the local weights of sub-criteria and the global weights of the related criteria. The global weights are shown in Table 4.

Table 4. Global Weights of The Criteria

Criteria	Sub-criteria	Local weights	Global weights
Price (C1 = 0.27)	Unit cost (C11)	0.52	0.14
	Holding cost (C12)	0.28	0.08
	Ordering cost (C13)	0.20	0.05
Criticality (C2 = 0.39)	Annual demand (C21)	0.75	0.29
	Availability (C22)	0.25	0.10
Storage ability (C3 = 0.16)	Expiry date (C31)	0.71	0.11
	Storage ability(C32)	0.29	0.05
Procurement Process (C4 = 0.18)	Lead time (C41)	0.56	0.10
	Pack size (C42)	0.27	0.05
	Minimum order quantity(C43)	0.17	0.03

Global weights of sub-criteria and data for each inventory item based on the sub-criteria were calculated by using TOPSIS to obtain composite priority weight for each inventory item. The inventory items are then classified using traditional ABC classification technique. After careful consideration, the authors of this paper and the management of the company decided that the borders between classes are determined based on

Pareto Principle. Therefore, the borders between classes were derived from the following basis. Class A involves 80% of the cumulative composite priority weights. Class B involves 15% of the cumulative composite priority weights while 5% of total composite priority weights belong to class C. Table 5 shows the classification of 69 inventory items of the company.

Table 5. Multi-Criteria Classification Result

Item	Weights	Relative weights	Cumulative weights	Class	Item	Weights	Relative weights	Cumulative weights	Class
S-1	0.646	17.75%	17.75%	A	S-10	0.017	0.47%	95.63%	C
S-54	0.523	14.37%	32.12%	A	S-53	0.017	0.47%	96.10%	C
S-3	0.361	9.93%	42.04%	A	S-36	0.017	0.47%	96.57%	C
S-28	0.281	7.73%	49.77%	A	S-47	0.017	0.47%	97.03%	C
S-2	0.281	7.73%	57.50%	A	S-67	0.017	0.47%	97.50%	C
S-8	0.228	6.27%	63.77%	A	S-61	0.013	0.35%	97.86%	C
S-14	0.152	4.18%	67.94%	A	S-41	0.012	0.34%	98.20%	C
S-42	0.102	2.79%	70.74%	A	S-65	0.009	0.25%	98.45%	C
S-62	0.098	2.70%	73.44%	A	S-6	0.004	0.11%	98.56%	C
S-15	0.098	2.69%	76.13%	A	S-57	0.003	0.09%	98.66%	C
S-55	0.077	2.13%	78.26%	A	S-51	0.003	0.09%	98.75%	C
S-39	0.072	1.98%	80.24%	A	S-23	0.003	0.09%	98.84%	C
S-33	0.056	1.54%	81.79%	B	S-56	0.003	0.09%	98.94%	C
S-4	0.051	1.41%	83.20%	B	S-52	0.003	0.09%	99.03%	C
S-7	0.034	0.95%	84.14%	B	S-35	0.003	0.09%	99.12%	C
S-9	0.029	0.81%	84.95%	B	S-20	0.003	0.09%	99.21%	C
S-68	0.029	0.80%	85.75%	B	S-29	0.003	0.09%	99.31%	C
S-24	0.029	0.78%	86.54%	B	S-38	0.003	0.09%	99.40%	C
S-64	0.025	0.69%	87.23%	B	S-34	0.003	0.09%	99.48%	C
S-30	0.025	0.69%	87.92%	B	S-26	0.002	0.07%	99.55%	C
S-32	0.023	0.63%	88.55%	B	S-22	0.002	0.06%	99.62%	C
S-63	0.023	0.63%	89.18%	B	S-44	0.002	0.06%	99.68%	C
S-40	0.020	0.56%	89.74%	B	S-60	0.002	0.06%	99.74%	C
S-18	0.019	0.53%	90.27%	B	S-50	0.002	0.06%	99.81%	C
S-66	0.019	0.52%	90.78%	B	S-49	0.002	0.06%	99.87%	C
S-48	0.019	0.52%	91.30%	B	S-58	0.002	0.06%	99.94%	C
S-46	0.019	0.52%	91.82%	B	S-11	0.002	0.05%	99.99%	C
S-17	0.019	0.52%	92.33%	B	S-31	0.002	0.01%	99.99%	C
S-69	0.017	0.48%	92.81%	B	S-5	0.000	0.00%	100.00%	C
S-45	0.017	0.47%	93.28%	B	S-37	0.000	0.00%	100.00%	C
S-16	0.017	0.47%	93.75%	B	S-19	0.000	0.00%	100.00%	C
S-27	0.017	0.47%	94.22%	B	S-59	0.000	0.00%	100.00%	C
S-43	0.017	0.47%	94.69%	B	S-12	0.000	0.00%	100.00%	C
S-13	0.017	0.47%	95.16%	B	S-25	0.000	0.00%	100.00%	C
					S-21	0.000	0.00%	100.00%	C

4.2. The Proposed Inventory Model

Based on the inventory classification in Table 5, the 12 Class A items will be designed for their inventory model. Using Arena Input Analyzer software yields various types of lead time demand distribution of the items: normal distribution for item S-54, S-8, S-14, S-15 and S-39; uniform distribution for item S-1, S-42, S-62 and S-55; lognormal distribution for item S-3 and S-28; and exponential distribution for item S-2.

Decision support system was designed to support decision makers in using the proposed model efficiently. It was designed using Microsoft Excel-VBA software that integrates Microsoft Visual Basic and Microsoft Excel. By translating the fuzzy formulation of continuous review inventory model in Visual Basic programming code, the decision support system was successfully constructed.

Since the finding of the four types of lead-time demand distribution for class A items, the formulations to determine the expected stock out demand per cycle ($n(R)$) and the reorder point (R) will be different. Therefore, we designed four function procedures in Visual Basic programming code for each distribution type: normal, uniform, lognormal, and exponential distribution model. Each function procedure was used to determine the inventory model decision variable: optimal order quantity (Q),

reorder point (R), and the estimated total inventory cost ($C(Q,r)$).

The main interface window of decision support system in Microsoft Excel-VBA is given in Figure 3. To run these decisions support system, the user should select an inventory item which will be calculating and fill in the text boxes of annual demand and fuzzy inventory cost. The user can also change the value of the parameter of distribution and pack size. It can be accessed at the “sheet2” in the Microsoft Excel-VBA.

CONTINUOUS REVIEW INVENTORY MODEL				
Inventory Item	S-39			
Annual Demand	10309.81 KG/Year			
Lead time demand distribution of S-39 is NORMAL with:				
Mean:	684 KG			
Standard Deviation:	223 KG			
Trapezoidal fuzzy costs				
	a	b	c	d
Unit cost	0.665	0.700	0.770	0.805 USD/KG
Holding cost	0.343	0.350	0.368	0.373 USD/KG/Year
Ordering cost	2.511	2.643	2.907	3.040 USD/Order
Penalty cost	0.13	0.14	0.16	0.17 USD/KG
Hasil				
Optimal Order Quantity (Q)	500 KG/Order			
Optimal Reorder Point (R)	952.53 KG			
Total Cost	8067.24 USD/Year			
				SOLVE
				CLEAR ALL

Figure 3. The main interface window of decision support system

By using the decision support system, the optimal order quantity (Q), reorder point

(R), and total inventory cost of the proposed model resumed in Table 6.

Table 6. The Decision Variables of The Proposed Model

Item	Optimal Order Quantity (Kg/order)	Reorder point (Kg)	Total inventory cost (USD/year)
S-1	2075	7368.8	1,374,538.72
S-54	950	3178.84	90,435.67
S-3	20.8	16.14	1,648.57
S-28	45	14.7	4,716.03
S-2	50	9.02	5,574.12
S-8	486	1045.34	57,316.17
S-14	50	44.7	17,835.36
S-42	25	158.27	87,991.83
S-62	1050	137.94	85,616.14
S-15	725	1378.73	28,396.19
S-55	25	77	43,894.11
S-39	500	952.53	8,067.24

Comparison of Inventory Turnover Ratio (ITR) and inventory total cost between the existing and proposed model is shown in Table 7.

Table 7. Comparison Between The Existing and Proposed Model

Item	Inventory Turnover Ratio (ITR)		Inventory Total Cost (USD/Year)		Percentage of savings (%)
	Existing model	Proposed model	Existing model	Proposed model	
S-1	3,88	4,28	1.375.141	1.374.539	0,04
S-54	19,87	22,83	92.574	90.436	2,36
S-3	0,53	6,73	5.923	1.649	259,29
S-28	6,78	7,11	17.894	4.716	279,43
S-2	0,70	5,05	9.364	5.574	67,99
S-8	6,97	11,82	67.784	57.316	18,26
S-14	0,79	1,34	47.721	17.835	167,57
S-42	2,92	7,05	123.800	87.992	40,69
S-62	6,08	8,17	108.870	85.616	27,16
S-15	3,49	7,74	28.529	28.396	0,47
S-55	2,39	6,74	73.570	43.894	67,61
S-39	5,05	8,57	8.198	8.067	1,62
Total			1.959.3681	1.806.030	77,71

5. Discussion

The fuzzy continuous review inventory model using multi-criteria ABC classification approaches is presented in this study to the answer the research question. In classifying the 69 inventory items, ten relevant sub-criteria to the subject of research had been selected. Using the FANP techniques, this

research found that annual demand sub-criterion has the highest importance weight in the inventory. It means that the use of dollar usage in traditional ABC classification proved to be irrelevant in real life. This research also found pack size sub-criterion as a new criterion in the ABC multi-criteria classification research.

The ABC classification based on ten sub-criteria in this research was constructed three inventory classes. The result of this research (as shown in Table 5) by using Pareto principle shows that among 69 items, 12 items (17% of all items) are identified as class A or outstandingly important group, 22 items as class B (32% of all items) as class B or average important group, and the remaining 35 items as class C or relatively unimportant group as a basis for a control scheme. In terms of the number of items per class, this research shows that inventory items that have the highest priority weight will go into class A while inventory items that have the lowest weight will go into the class C and it contains 51% of all items.

These results provide a recommendation for a manager or the manager to start implementing the classification system on their company, so attentions to each inventory item given proportionally. Fuzzy continuous review inventory model has also presented in this research. Before design the model, it was found that from 12 class A items, four items have lead time demand distribution that shaped uniform, five items have normal distribution, two items have lognormal distribution, and an item has exponential distribution. The various types of lead-time demand distributions make this research relevant to the real life situations.

This research also proved that the previous researchers that generally used "assumptions" in determining the type of distribution is a less relevant method to the real life situations. For example, Godwin *et al.* (2013) who designed a continuous review inventory model in a company in Nigeria assumes all of the inventory items had uniform lead-time demand distribution, or Sadi-Nezhad *et al.* (2011) who designed the periodic and continuous review inventory model on transformer manufacturing in Iran assume that the lead-time demand distribution is entirely normal. The assumption of lead-time demand distribution is becoming irrelevant because

the differences in the distribution type will affect the mathematical formulation of the expected number of shortage and the value of decision variables.

In developing a practice model for the manager, a decision support system using Microsoft Excel-VBA is presented as the main result of fuzzy continuous review inventory model in this research (as shown in Figure 3). By using this decision support system, the manager can make rapid and accurate decisions. The value of decision variables: optimal order quantity (Q) reorder points (R), inventory total cost have been determined (as shown in Table 6). This research found that reorder point value of each inventory item has a higher value than expected lead-time demand. This means that safety stocks were prepared in this proposed model.

Comparison of Inventory Turnover Ratio (ITR) and inventory total cost between the existing and proposed model have been provided (as shown in Table 7). ITR comparison shows that the proposed model has a higher ratio than the existing model for each Class A item. According to Rao *et al.* (2009) and Bahagia (2006: 42), incremental of ITR showed an improvement on inventory management in reducing the overstocking level because of the increase in inventory turnover per cycle. Inventory total cost comparison shows that the proposed model has a lower total cost than the existing model for each Class A item. This result also shows that the proposed continuous review inventory model gives average savings of 77.7% compared to an existing model that was used by the company.

Finally, the ABC multi-criteria classification approach to design appropriate inventory model was supported by Aisyati *et al.* (2013) research. Aisyati *et al.* (2013) who used a continuous review inventory model for class A and B found that there are several items show that existing model performs better

than continuous review model or it can be said that the percentage of saving is negative. In their analysis, Aisyati *et al.* (2013) explained that the continuous review model might be failing to result in or result from better inventory model since the demand of the items is too lumpy or it has pattern of Poisson lead-time demand distribution. Aisyati *et al.* (2013) also recommended that this Poisson demand could be managed by periodic review inventory model. This finding is caused by the classification technique. Aisyati *et al.* (2013) used traditional ABC classification in their research. It means that the class A items are high-value inventory based on the dollar usage only. Consequently, although the demand of a high-cost item is too lumpy, it will be classified as class A. Therefore, the findings of this research, the positive percentage of saving of each class an items prove that the design of the inventory model using ABC multi-criteria classification approach would be more effective in saving the inventory cost than using traditional ABC classification.

6. Conclusion and Future Research

6.1. Conclusion

Based on the study, it can be concluded that Combination of Fuzzy Analytic Network Process (FANP) and *Technique of Order Preferences by Similarity to the Ideal Solution* (TOPSIS) in ABC multi-criteria classification techniques *identified 12 items of 69 inventory items as class A (outstandingly important class. They contribute to 80% total inventory cost. Furthermore, the appropriate inventory model for class A items is fuzzy continuous review inventory model using trapezoidal fuzzy numbers and the statistical testing of lead time demand distribution. This proposed inventory model increase the inventory turn ratio and reduce the inventory total cost with average savings of 78% for each inventory item. These findings show that the proposed model is feasible to be implemented in the company.*

6.2. Future Research

Future research can look at designing the appropriate inventory control model for more than one company or more than one class item. An inventory control model that also consider several factors such the decay factor, partial delivery from suppliers, and warehouse capacity constraint can also be designed in future research. Future research can also look to design an inventory-model or the inventory-model decision support system using demand-forecasting approach.

6.3. Contribution

This researched expected to contribute to the development of inventory management in real situations. The combination of FANP, TOPSIS, and traditional ABC classification technique found as an effective combination technique to classify the inventory items, especially a relatively large amount of inventory. a previous or the previous study, the graded mean integral representation defuzzification technique and trapezoidal membership function were just applied the indeterministic or an indeterministic model. Therefore, applying this defuzzification technique and membership function is the contribution of this research in stochastic inventory model environment. This research shows that the lead-time demand distribution is not always normally distributed and it needs to be testing before design the mathematical formulation of inventory model. Finally, the research that proposes a fuzzy continuous review inventory model with various types of lead-time demand distribution can also contribute to the mathematical formulation of inventory control models.

The other contribution of this research is that the inventory classification result gives a suggestion for the manager to develop an inventory control policy based on the importance level of the items. By implementing the proposed inventory model in this research, the enterprise should be able to reduce their overstocking level and inventory total cost. This research also

provided an inventory model decision support system for the company so managers can make rapid and accurate decisions.

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